

# VIBRATION-BASED METHODOLOGY FOR ONLINE HEALTH MONITORING OF ROTATING MACHINES

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Vibration-based condition monitoring represents the most efficient technology for early prediction and detection of failures in rotating machines. Faults can be detected by extracting typical features of vibration signature and comparing them to known thresholds of acceptable behaviour. Defining appropriate limit thresholds independently of the operating conditions, in order to perform a real time monitoring of any faulty state in system operation, is often a task not easy to achieve. The paper aims at presenting in this sense an effective condition monitoring technique for rotating machines, relying on a black box modelling approach of system dynamic behaviour. The powerful capabilities of the methodology are highlighted by implementing the model for a typical problem of rotating machines fault diagnosis. The proposed approach involves first identifying a Nonlinear ARX model, trained using the data from the healthy (nominal) operation of the machine. The model is then used for simulation of system known dynamics, to compute residuals by subtracting the model-produced outputs from the corresponding measured signals. Through an accurate monitoring of the properties of residuals, such as their mean, variance and root mean square, the method is able to successfully distinguish normal and faulty operations as well as to properly rank fault severity. The high mode-discrimination power of each considered residuals feature demonstrates the robustness of the technique and its attractiveness to face with rotating machines health monitoring problems.

Keywords: vibration, health monitoring, residual analysis.

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## 1. Introduction

As part of condition-based maintenance, machine condition monitoring is recognized as the most efficient strategy for carrying out maintenance in a wide variety of industrial applications. Condition monitoring stands for monitoring the current condition and predicting the future condition of machines while in operation. Accordingly, information about internal effects needs to be obtained externally while the machines are in operation. One of the main techniques for obtaining information from the inside of operating machines is vibration analysis [1-2-3]. Machines in normal condition have a characteristic vibration signature [4]. Most faults change this signature in a well-defined way, carrying information about the condition of the operating machine. While the increasing amplitude of vibration signature may provide an indication of the fault severity, the frequency can reveal the source of the defect [5]. The major economic benefits of vibration-based condition monitoring lie in predicting incipient faults well in advance, allowing repairs to be planned, spare parts to be acquired, and in particular avoiding losses in production [4].

In this regard, the paper aims at presenting a diagnostic technique, based on vibration analysis, for the first phase of machine condition monitoring that is fault detection, which precedes the subsequent phases of fault diagnosis and prognosis. In particular, the technique is designed for fault detection in rotating machines and is based on a model-based approach.

In general, model-based methods of fault detection make use of the relations among several measured variables to extract information about possible changes caused by faults. These relations, linking the measured input signals to the output signals, are represented by a mathematical process model. Fault detection methods then extract special features, like parameters, state variables or residuals. By comparing the observed features with their nominal values, analytical symptoms are generated which are the basis for fault diagnosis [6]. In the ideal case the features should only be influenced by the faults to be detected. However, because of the existence of modelling errors, unknown input signals, stationary and nonstationary disturbances at the outputs, the features value will vary continuously. Therefore, making the features sensitive to faults and robust against disturbing effects is still a tricky task.

On that basis, in the proposed methodology, the dynamic vibratory behaviour of a rotating machine in operation over a range of operating points is modelled by means of black-box system identification techniques. The nonlinear model, based on measurements of input signals (the machine operating parameters as speed and load) and output signals (the machine casing vibration) in machine healthy (nominal) conditions, is then used to implement a residual based fault detection. The model residues, computed as the difference between the future measured and model-produced signals, and their derived features provide diagnostic information ensuring faults detection. Besides, a proper data pre-processing allows to maximize the fault sensitivity of residuals, leading to the definition of a constant limit threshold with varying speed.

In the work, the key steps of the proposed model-based technique are fully described, and the approach is validated using experimental data acquired in a pump cavitation test.

## 2. Vibration-based condition monitoring

Many machines containing drive systems with motors, clutches, gears, shafts, belts or chains, and bearings, usually generate vibrations owing to possible inherent machine oscillations, shaft oscillations with radial or axial displacement, irregular speed of the shaft, torsional shaft oscillation, impulsive excitation [6]. While some vibrations indicate a normal state of the machines, the changes they could undergo and the introduction of new ones may be caused by faults. Hence, vibration analysis is a well-established technique in the field of machines monitoring or supervision, also for the several advantages compared with the other methods [1]. It reacts immediately to change and can therefore be used for permanent as well as intermittent monitoring. Often, it is able to point to the actual faulty component. In addition, most importantly, many powerful signal processing techniques can be applied to vibration signals to extract even very weak fault indications from noise and other masking signals.

The goal of vibration analysis is to extract condition information from the measurements in terms of suitable features to be used for fault detection and diagnosis, taking into account that the measured vibration signals are always a combination of source effects and transmission path effects.

## 3. Rotating machines fault detection by residual analysis

In rotating machines, several faults manifest themselves at frequencies corresponding to the speed of the shaft and its harmonics [4]. The arising frequencies therefore depend on the rotational speed.

Referring to Fig. 1, a general overview of the proposed model-based fault detection method for rotating machines is shown.

The first stage of the methodology basically involves the development of the model on the basis of data acquired when machine operates in healthy conditions, properly processed. Of course, both input (speed and load) and output (casing vibration) data need to be included. The process model thus describes the nominal or non-faulty vibration behaviour of the machine depending on its operating conditions. Prior to model identification, an accurate processing of collected data is required, depending on the nature of the specific machine fault to investigate. This makes the model able to capture only those behaviours that will be more susceptible to change when fault occurs. Once the model is identified, the subsequent residual analysis aims at quantifying the discrepancies between the process and the model, investigating the most suitable residue features to be monitored. The application of model formulation to all acquired data allows to finally validate the process model and to define a limit threshold for fault detection and isolation, based on the comparison between healthy and faulty residue feature values. As a result, by integrating the built model in a real online condition monitoring procedure, any fault condition can be detected if the actual residue feature value overcomes the defined threshold.

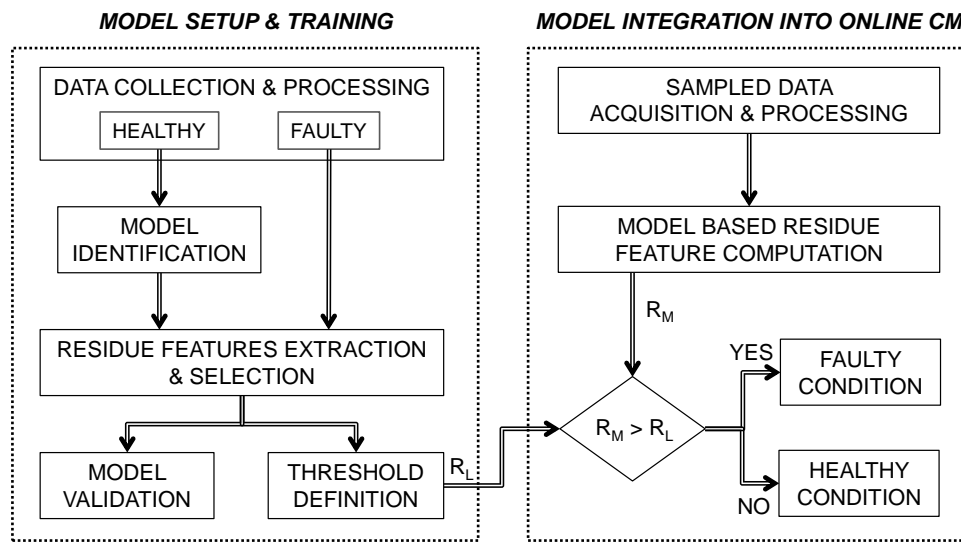


Figure 1: Step-by-step procedure for residue based fault detection.

In the following, a more detailed description of the fundamental stages of the procedure is given.

### 3.1 Model identification

Mathematical models of dynamic processes are primarily obtained by either theoretical/physical modelling or experimentally by identification methods [6]. The proposed approach is based on this latter option. The mathematical model of the process is obtained from measurements of input and output signals, evaluated by means of suitable identification methods. Even though such experimental models contain parameters as numeric values whose functional relation with the physical basic data of the process remains unknown, in many cases they ensure a more exact description of the real dynamic behaviour of the system, often determined with less expenditure with respect to physical models. In this case, a so-called black-box modelling procedure is thus utilized, which involves the identification of a nonlinear model based on measurable input and output signals of the rotating machine in operation. According to the proposed method, artificial neural networks are adopted as nonlinearity estimators rather than a classical approach based on polynomial approximations. Neural networks based methods in the form of flexible nonlinear functions do not require specific knowledge on the process structure, allowing to extend

the algorithm applicability to the modelling of complex nonlinear static and dynamic behaviours, as in the case of vibration generation in rotating machinery.

### 3.2 Residue generation and feature extraction

The methodology relies then on comparing the process behaviour with the process model describing the nominal behaviour, in order to detect possible faults in the process. The residuals are thus computed, as the difference between the measured signal and the corresponding model-produced output.

The ultimate goal is to extract suitable features from residual signals for fault isolation. Since no parametric information is available, features purely derived from signal properties, such as maximum amplitude or variance of the signal, are considered. After identifying the most sensitive residues features, the implementation of the process model on the overall acquired data allows to validate the model itself, as well as to define an appropriate threshold representing the limit for fault onset. The threshold will assume a constant value independently of the machine operating condition.

### 3.3 Fault detection design

The model integration within a real time condition monitoring procedure can now be realized. Data from time to time sampled are acquired and processed, on the basis of the stored model their residues feature value is computed and compared to the tuned threshold. An online monitoring of the investigated fault condition can be thus performed directly in the operating machine. It is worth to note that the algorithm architecture may be extended for the detection of different types of fault. In this case, the algorithm would work in parallel by processing acquired data in a different way and applying a different process model to obtain residues, depending on the particular fault condition to investigate.

## 4. Case study: pump cavitation detection

Pumps are basic components in most technical processes. Since pumps health affects the overall reliability and safety of many plants, their supervision and fault diagnosis are of relatively high importance [7]. In this section, the outcomes of the above described approach, used for the detection of a typical issue affecting the performance of pumping systems, are presented and discussed.

One of the most important causes for faults to pumps, leading at least to interruptions of operation or maintenance, is cavitation phenomenon. Cavitation consists in the development of vapour bubbles inside the fluid if static pressure falls below vapour pressure. Bubbles collapse abruptly leading to damage at the blade wheels and generating crackling sound. Of course, the supervision of pumps depends very much on the applied instrumentation. Various research efforts have shown that the application of vibration sensors for studying pump behaviour under the influence of cavitation allows a correct fault diagnosis as well as an early fault detection [8-9-10-11-12].

In this sense, the developed fault detection method has been applied to experimental data acquired on a gear pump for automotive applications, tested on a dedicated test bench in healthy and faulty conditions. In particular a pump faulty operation was induced by forcing cavitation to occur through the setting of a calibrated orifice at the suction side of the component. Specifically, data were collected for different shaft speed, from 1000 to 5000 rpm (step 1000 rpm), for a fixed oil temperature, by varying the suction pressure from a no cavitation value (regular diameter of the inlet port) to a cavitation value (inlet port restriction) while keeping constant the delivery pressure. During experiments, main operating parameters of the pumping system, i.e. the oil flow rate, the shaft speed, the oil temperature, the pressure ripples in a shaft rotation, the mean suction and delivery pressures, were carefully monitored. The pump behaviour under the influence of induced fault was investigated in the different tested conditions by means of a high frequency ceramic shear ICP® accelerometer, adhesively mounted on the pump casing in the area of suction chamber.

As an example, in Fig. 2 the spectra highlight the large deviations introduced by cavitation in the spectral content of the vibration signals at 3000 and 4000 rpm. This most occurs at the high frequencies, in particular within the frequency range comprised approximately between 7 and 11 kHz, where the faulty signals exhibit higher amplitudes with respect to the normal operation.

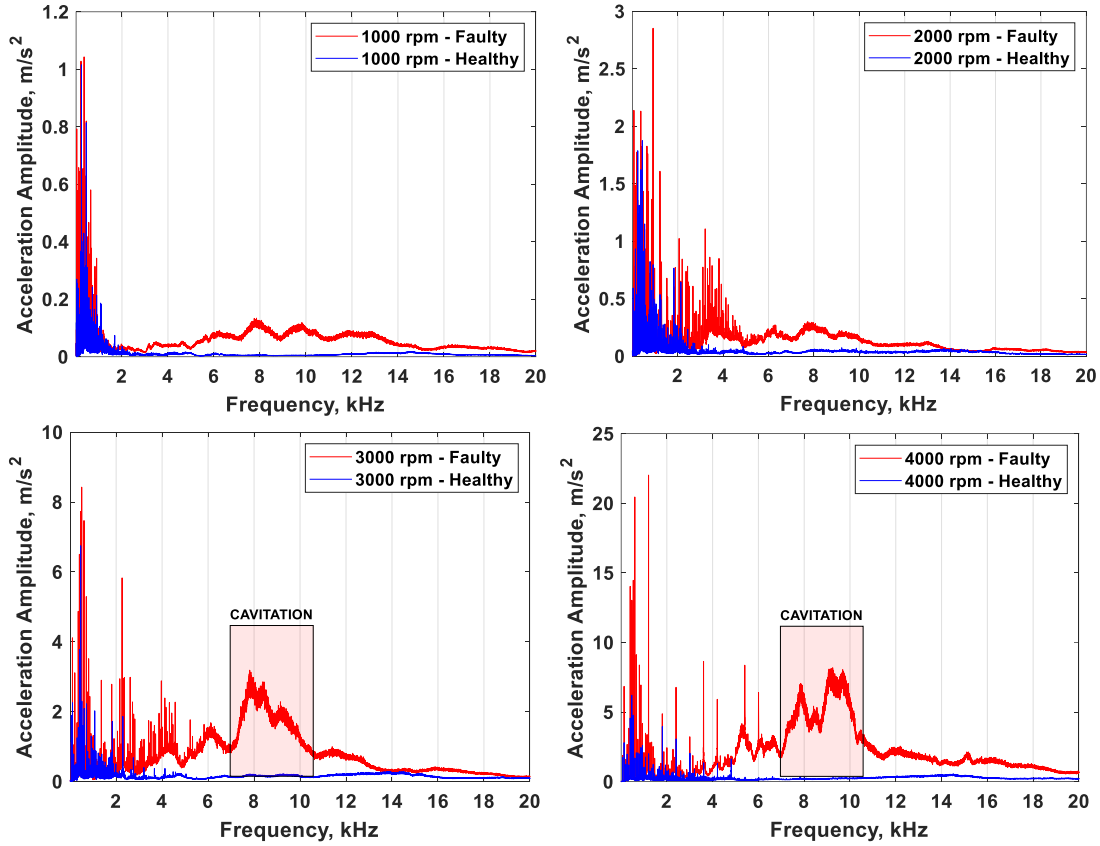


Figure 2: Vibration spectra comparison in healthy/faulty pump operation at 1000-2000-3000-4000 rpm.

Spectral analysis provided an insight into the typical frequencies of interest of the phenomenon, useful for the initial processing phase to be performed on the acquired data, as reported in Fig. 1. The overall procedure was then step-by-step applied, to set-up a real time monitoring of cavitation-induced faults in the tested pump.

A dynamic model of pump behaviour was identified, by regressing the measured vibration values on the previous vibration and shaft speed measurements. In detail, a Nonlinear ARX model was employed to fit the time-domain data acquired in non-fault conditions and then processed. The model structure was thus configured to have as output and input channels respectively the acceleration and the pump speed time series. Separate data sets were used for estimating and validating the model. The model orders and delays, defining the regressor configuration, the nonlinearity estimator and the estimation algorithm were properly tuned in order to obtain the best model validation, by comparing the model-predicted output and the measured output in terms of normalized root mean squared error (NRMSE), i.e. the percent fit to estimation data.

The residues of the model were finally computed, as the difference between the measured acceleration signal properly processed and the corresponding model-produced output. Residual data were calculated for each ensemble and each mode of operation. Different properties of residuals were then investigated to distinguish between normal and faulty operation. Suitable features were extracted, derived purely from residual signal properties: maximum amplitude, root-mean-square level, variance, mean, maximum-to-

minimum difference and mean absolute deviation. In order to analyse the mode-discrimination power of the considered residue features, features data were visualized as scatter plots reported in Fig. 3.

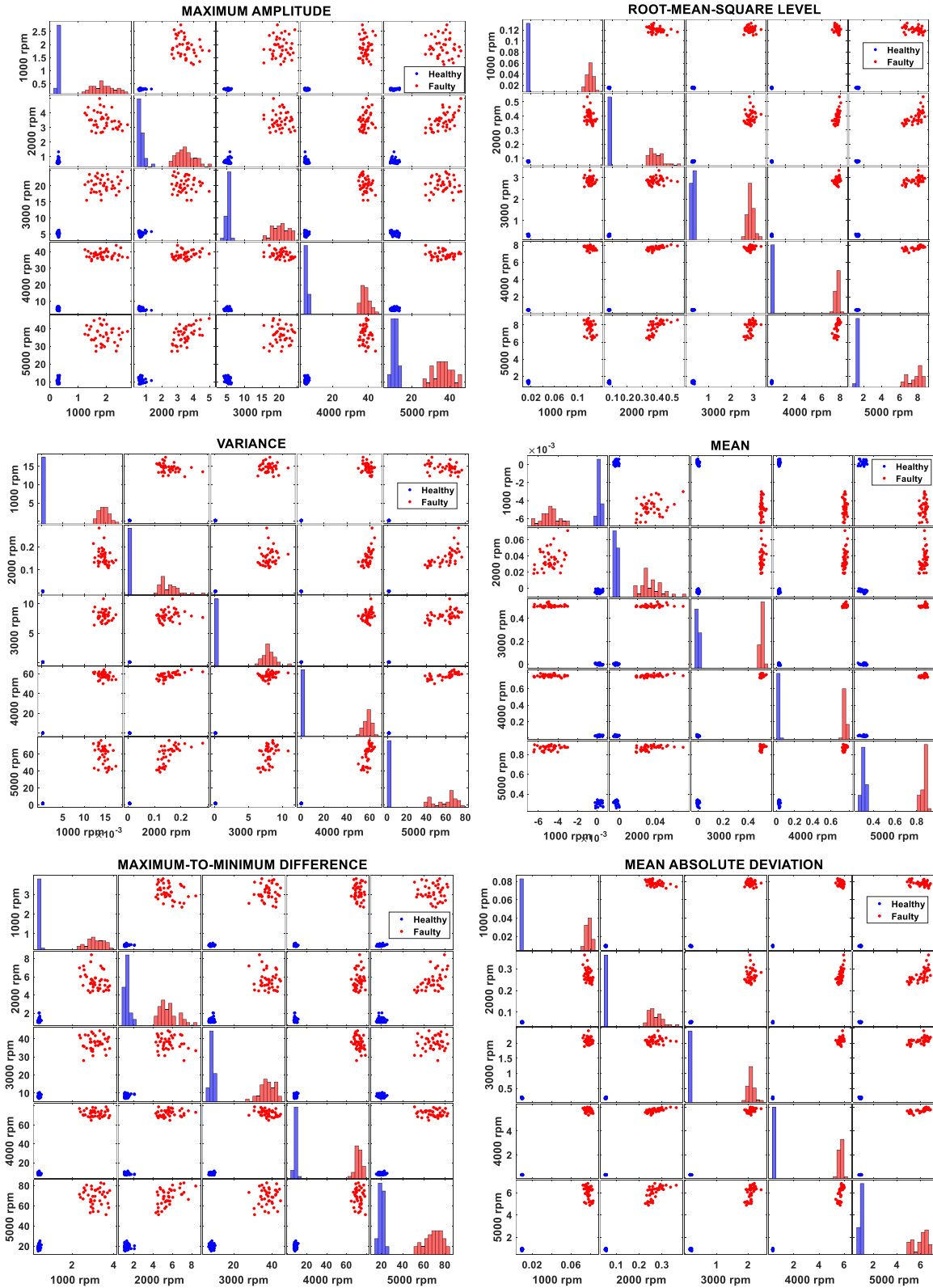


Figure 3: Scatter plots of residues features in all considered pump operating conditions.



The plots show that each feature allows to clearly separate healthy mode to faulty mode at all investigated speed conditions, thus making possible the detection of the faulty behaviour. Fault isolation could also be ensured, thanks to data pre-processing which makes the model affected only by the specific investigated fault. Despite the high mode-discrimination power of each considered residuals feature, for its very low dispersion root-mean-square level was selected as the most suitable feature to be tracked during a real time condition monitoring of pump operation. Figure 4 reports RMS of residues for 40 successive time samples of duration 1 second at all investigated pump speeds in each mode of operation. As can be observed, results are in accordance with spectral analysis outcomes, and prove that the model in addition to successfully distinguish healthy and faulty operations is able to properly rank fault severity. The coherence of obtained results allows to inherently define a unique limit threshold for healthy/faulty classification, validating the used approach.

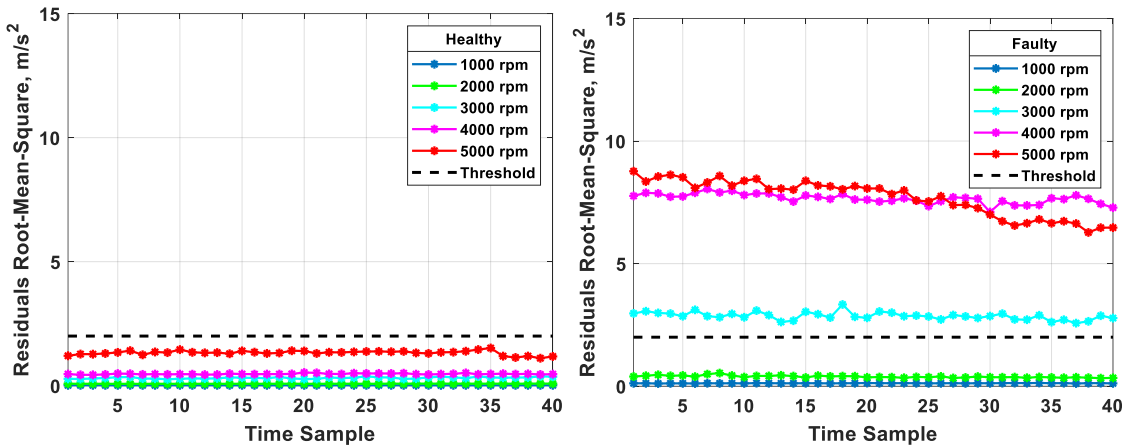


Figure 4: Residues Root-Mean-Square for 40 successive time samples at all investigated pump speeds: threshold definition for healthy/faulty classification.

To give a results overview, mean values of residues RMS were computed over the 40 successive time samples. In Fig. 5 averages are shown against pump speed in both operation modes. Even though a larger dataset is needed in order to cover the whole pump operation range enhancing the model accuracy, the outlined polylines suggest a possible trend of pump cavitation behaviour as a function of speed conditions. It is noteworthy that the highly increasing cavitation level between 3000 and 4000 rpm followed by a steady level over 4000 rpm is substantially confirmed by vibration spectral analysis.

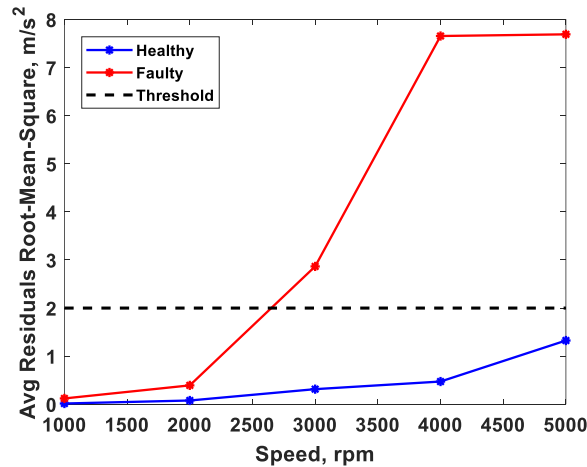


Figure 5: Mean of Residues Root-Mean-Square over 40 successive time samples as a function of pump speed.

## 5. Conclusion

In this paper, a vibration-based methodology for the online condition monitoring of rotating machines has been presented. The method makes use of a nonlinear modelling approach based on the use of Artificial Neural Networks for the identification of the healthy-state vibration behaviour of rotating machines, to then implement a residual based fault detection. The proposed technique, applied for a typical fault detection problem, proves capable of detecting and isolate faults ensuring the definition of a constant limit threshold, regardless of the machine operating condition. This is achieved through a proper data pre-processing for synthesizing in the model only those behaviours more susceptible to change when fault occurs. In this sense, the proposed approach offers flexibility, as data pre-processing can be adapted to the fault to be investigated. Of course, the model can be further enhanced in order to diagnose faults under machine transient operating conditions. Once validated over different types of fault, the technique could be an effective and robust tool in the detection and diagnosis of faults and it may yield an effective solution for the online condition monitoring of rotating machines.

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## REFERENCES

- 1 Randall, R. B. *Vibration-based condition monitoring: industrial, aerospace and automotive applications*. John Wiley & Sons (2011).
- 2 Casoli, P., Pastori, M., Scolari, F., & Rundo, M. A Vibration Signal-Based Method for Fault Identification and Classification in Hydraulic Axial Piston Pumps. *Energies*, **12**(5), 953 (2019).
- 3 Razak, N. F. D., Sani, M. S. M., Azmi, W. H., & Zhang, B. The Effect of Change in Flowrate on Power Spectral Density (PSD) of Automotive Radiator System for Flow-Induced Vibration Monitoring. In *IOP Conference Series: Materials Science and Engineering* (Vol. **469**, No. 1, p. 012101). IOP Publishing (2019, January).
- 4 Crocker, M. J. Ed., *Handbook of Noise and Vibration Control*, John Wiley & Sons, Hoboken, NJ (2007).
- 5 Goyal, D., & Pabla, B. S. The vibration monitoring methods and signal processing techniques for structural health monitoring: A review. *Archives of Computational Methods in Engineering*, **23**(4), 585-594 (2016).
- 6 Isermann, R. *Fault-diagnosis systems: an introduction from fault detection to fault tolerance*. Springer Science & Business Media (2006).
- 7 Isermann, R. *Fault-diagnosis applications: model-based condition monitoring: actuators, drives, machinery, plants, sensors, and fault-tolerant systems*. Springer Science & Business Media (2011).
- 8 Battarra, M., & Mucchi, E. Incipient cavitation detection in external gear pumps by means of vibro-acoustic measurements. *Measurement*, **129**, 51-61 (2018).
- 9 Siano, D., & Panza, M. A. Diagnostic method by using vibration analysis for pump fault detection. *Energy Procedia*, **148**, 10-17 (2018).
- 10 Buono, D., Siano, D., Frosina, E., & Senatore, A. Gerotor pump cavitation monitoring and fault diagnosis using vibration analysis through the employment of auto-regressive-moving-average technique. *Simulation Modelling Practice and Theory*, **71**, 61-82 (2017).
- 11 Siano, D., Frosina, E., & Senatore, A. Diagnostic Process by Using Vibrational Sensors for Monitoring Cavitation Phenomena in a Gerotor Pump Used for Automotive Applications. *Energy Procedia*, **126**, 1115-1122 (2017).
- 12 Cucit, V., Burlon, F., Fenu, G., Furlanetto, R., Pellegrino, F. A., & Simonato, M. A control system for preventing cavitation of centrifugal pumps. *Energy Procedia*, **148**, 242-249 (2018).